

The Dark Side of Galaxy Color: evidence from new SDSS measurements of galaxy clustering and lensing

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ABSTRACT

The age matching model has recently been shown to predict correctly the luminosity L and $g - r$ color of galaxies residing within dark matter halos. The central tenet of the model is intuitive: older halos tend to host galaxies with older stellar populations. In this paper, we demonstrate that age matching also correctly predicts the $g - r$ color trends exhibited in a wide variety of statistics of the galaxy distribution for stellar mass M_* threshold samples. In particular, we present new measurements of the galaxy two-point correlation function and the galaxy–galaxy lensing signal $\Delta\Sigma$ as a function of M_* and $g - r$ color from the Sloan Digital Sky Survey, and show that age matching exhibits remarkable agreement with these and other statistics of low-redshift galaxies. We describe how age matching is a specific example of a larger class of Conditional Abundance Matching models (CAM), a theoretical framework we introduce here for the first time. CAM provides a general formalism to study correlations at fixed mass between *any* galaxy property and *any* halo property. The striking success of our simple implementation of CAM provides compelling evidence that this technique has the potential to describe the same set of data as alternative models, but with a dramatic reduction in the required number of parameters. CAM achieves this reduction by exploiting the capability of contemporary N-body simulations to determine dark matter halo properties other than mass alone, which distinguishes our model from conventional approaches to the galaxy-halo connection.

Key words: cosmology: theory — dark matter — galaxies: halos — galaxies: evolution — galaxies: clustering — large-scale structure of universe

1 INTRODUCTION

Extensive effort has been put forth to understand how the star formation activity in galaxies maps to dark matter halos in a cosmological context, typically via galaxy color (Zehavi et al. 2005, 2011; Skibba & Sheth 2009; Tinker & Wetzel 2010; Wang et al. 2007; Krause et al. 2013; Gerke et al. 2012; Masaki et al. 2013; Hearin & Watson 2013). Color is a commonly employed observable as it is correlates well with the star formation history

of a galaxy: blue galaxies exhibit ongoing star formation, and conversely, red galaxies are typically not actively forming stars. Observations have long shown that redder galaxies preferentially occupy more dense environments, while bluer galaxies tend to reside in underdense regions (Balogh et al. 1999; Blanton et al. 2005; Weinmann et al. 2006, 2009; Peng et al. 2010, 2012; Carollo et al. 2012). Additionally, there exists a clear bimodality in the distribution of galaxy colors, with distinct red (ellipsoidal) and blue (disk) populations (Blanton et al. 2003; Baldry et al. 2004; Blanton et al. 2005; Wyder et al. 2007). This segregation between galaxy populations is al-

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ready in place at $z \sim 1$ (Bell et al. 2004; Cooper et al. 2006, 2012) and possibly extends out to $z \sim 3$ (Whitaker et al. 2011).

Recently, Hearin & Watson (2013) introduced *age distribution matching* (or simply *age matching* for brevity), a new theoretical formalism for connecting galaxies to halos as a function of their color and luminosity. Age matching is rooted in the popular abundance matching technique, wherein the halo maximum circular velocity V_{\max} (or mass) is in monotonic correspondence with luminosity L (or stellar mass). This simple, yet powerful approach has been employed to describe a variety of observed galaxy statistics (e.g., Kravtsov et al. 2004; Vale & Ostriker 2004; Tasitsiomi et al. 2004; Vale & Ostriker 2006; Conroy et al. 2006; Conroy & Wechsler 2009; Guo et al. 2010; Simha et al. 2010; Neistein et al. 2010; Watson et al. 2012; Reddick et al. 2012; Rodríguez-Puebla et al. 2012; Hearin et al. 2012). However, traditional abundance matching does not capture well-established features in the galaxy distribution, such as color bi-modality, that reflect the complexity in the physics of galaxy evolution.

To that end, Hearin & Watson (2013) (hereafter Paper I) showed that by extending the traditional abundance matching formalism to consider an additional halo property beyond V_{\max} , the observed spatial distribution of galaxies as a function of luminosity *and* color could be accurately reproduced. Specifically, the authors considered the redshift, dubbed z_{starve} , that correlates with the epoch at which the star formation in the galaxy is likely stifled, ultimately leading to the quenching of the galaxy. By using merger trees to map the full mass assembly history (MAH) of halos, a halo’s z_{starve} value is determined by whichever of the following three events happens first in its MAH: (1) the epoch a halo accretes onto a larger halo, thus becoming a subhalo, (2) the epoch a halo reaches a characteristic mass¹, and (3) the epoch a halo transitioned from the fast- to slow-accretion regime. Under the simple assumption that z_{starve} correlates with $g-r$ color at fixed luminosity, the age matching technique was able to accurately predict color-dependent clustering in the Sloan Digital Sky Survey (SDSS: York et al. 2000; Abazajian et al. 2009) and a variety of galaxy group statistics. The success of the model supported the idea that the assembly history of galaxies and halos are correlated.

The central tenet of age matching is a simple one: older galaxies live in older halos. Of course, other halo proxies beyond z_{starve} can (and should) be investigated, thus age matching can be thought of as a specific implementation of a more general formalism we will call *Conditional Abundance Matching* or CAM. As we lay out in detail in § 4.3, CAM provides the framework for probing correlations between any galaxy property (e.g., color, star formation rate, morphology) and any additional halo property. For the purposes of this paper, we aim to test the predictions of age matching against a battery of new observational measurements from SDSS: including, *stellar mass*-dependent clustering and galaxy-galaxy lensing

as a function of color as well as galaxy group statistics based on an SDSS galaxy group catalog.

The paper is laid out as follows. In § 2 we discuss the data and new measurements incorporated throughout this work. In § 3 we discuss the simulation, halo catalogs, and merger trees. In § 4 we give an overview of our general methodology, including a description of how our SDSS-based mock catalog is constructed as well as an analytic presentation of CAM. A brief discussion of how we make predictions using CAM for various galaxy statistics is given in § 5. Results are presented in § 6, followed by a discussion and summary in § 7 & § 8, respectively. Throughout this work we assume a flat Λ CDM cosmological model with $\Omega_m = 0.27$ and all stellar masses are quoted with $h = 1$.

2 DATA AND MEASUREMENTS

2.1 SDSS Galaxy Sample

Our baseline galaxy catalog is a volume-limited sample of galaxies taken from the Main Galaxy Sample of Data Release 7 (Abazajian et al. (2009), DR7 hereafter) of SDSS. This is the DR7 update of the DR3 sample used in Berlind et al. (2006), to which we refer the reader for details. The effective volume of this subsample is $V_{\text{eff}} = 5.8 \times 10^6 h^{-3} \text{Mpc}^3$. These galaxies span the redshift range $0.02 \leq z \leq 0.068$; the upper redshift bound was determined by a completeness requirement in r -band absolute magnitude $M_r - 5 \log h < -19$, where M_r refers to Petrosian magnitude measurements. For convenience, we refer to this catalog as our “Mr19” catalog.

Stellar masses were taken from the MPA-JHU catalog, publicly available at <http://www.mpa-garching.mpg.de/SDSS/DR7>. The stellar masses in this catalog were estimated using the `kcorrect` code of Blanton & Roweis (2007), assuming a Chabrier IMF (Chabrier 2003). We study properties of galaxy samples constructed with stellar mass cuts at $\log_{10}(M_*) > [9.8, 10.2, 10.6]$ with stellar masses quoted in $h^{-2} M_\odot$. We refer to these as our $M_*^{9.8}$ catalog, our $M_*^{10.2}$ catalog, and our $M_*^{10.6}$ catalog, respectively. Each of these three stellar mass-limited samples were constructed from the Mr19 catalog. Using a $M_r - 5 \log h < -18$ volume-limited catalog constructed in the same fashion as our Mr19 sample, we estimate that the $M_*^{9.8}$ sample is $\sim 98\%$ complete in stellar mass.

For several of the statistics explored in this paper, we have divided our galaxy samples into “red” and “blue” subsamples. To do so, we adopt the convention of van den Bosch et al. (2008), separating the galaxies with the following stellar mass-dependent cut:

$$g - r = 0.76 + 0.15 [\log(M_*/(h^{-2} M_\odot)) - 10.0]. \quad (1)$$

2.2 Clustering Measurements

We measure the projected correlation function of these stellar mass threshold and color split samples in a way similar to Zehavi et al. (2011). We first count data-data, data-random, and random-random pairs as a function of line-of-sight separation π and projected separation

¹ Hearin & Watson (2013) tried several values for the characteristic mass and found $10^{12} h^{-1} M_\odot$ to be most compatible with the data

tion r_p in 15 logarithmically spaced bins of r_p in the range $0.1 - 20 h^{-1}\text{Mpc}$. We then use the Landy & Szalay (1993) estimator to evaluate the correlation function: $\xi(r_p, \pi) = (\text{DD} - 2\text{DR} + \text{RR})/\text{RR}$. We use a random catalog with one million points to measure DR and RR in order to ensure that Poisson errors in the random counts do not dominate the error budget. Next we integrate along the line-of-sight to compute the projected correlation function $w_p(r_p)$. Specifically, we integrate out to $\pi = 40 h^{-1}\text{Mpc}$, which is sufficient to remove most of the effect of redshift distortions. Finally, we compute errors in our measurements by jackknife resampling from 50 equal-area regions on the sky. Our measured correlation functions and error estimates for the full sample, as well as the red/blue samples, are listed in Tables 1-3.

2.3 Galaxy Group Sample

We construct a catalog of galaxy groups from the $M_{*}^{9.8}$ galaxy sample described in § 2.1 using the group-finder introduced in Berlind et al. (2006), to which we refer the interested reader for details. Briefly, this algorithm parses galaxies into groups via a friends-of-friends algorithm with different linking lengths in the transverse and line-of-sight direction; values of the linking lengths were chosen to optimize completeness and purity of the group sample. The algorithm has no regard for galaxy properties beyond their angular positions and redshifts. We define each group's central galaxy to be the group member with the largest stellar mass,² and satellite galaxies to be the remaining group members.

2.4 Galaxy-Galaxy Lensing Measurements

We compute the lensing signal in 23 logarithmic radial bins from 0.2 to $2 h^{-1}\text{Mpc}$ as a weighted summation over lens-source pairs, using the following estimator:

$$\Delta\Sigma(R) = \frac{\sum_{ls} w_{ls} \gamma_t^{(ls)} \Sigma_c^{(ls)}}{2\mathcal{R} \sum_{ls} w_{ls}}, \quad (2)$$

where γ_t is the tangential shear, and the critical surface density $\Sigma_c^{(ls)}$ is a geometric factor,

$$\Sigma_c^{(ls)} = \frac{c^2}{4\pi G} \frac{D_s}{D_l D_{ls} (1 + z_l)^2}. \quad (3)$$

Here, D_l and D_s are angular diameter distances to the lens and source, D_{ls} is the angular diameter distance between the lens and source, and the factor of $(1 + z_l)^{-2}$ arises due to our use of comoving coordinates. The factor of $2\mathcal{R}$ arises due to our definition of ellipticity and the shear responsivity \mathcal{R} is approximately $1 - e^2 \approx 0.87$ (Bernstein & Jarvis 2002). The weights are assigned according to the error on the shape measurement via

$$w_{ls} = \frac{(\Sigma_c^{(ls)})^{-2}}{\sigma_e^2 + \sigma_{SN}^2} \quad (4)$$

² See Skibba et al. (2011) for a discussion of the complicating factor that central galaxies are not always the brightest group members.

where σ_e is the estimated shape error per component and σ_{SN} is the intrinsic shape noise per component, which was determined as a function of magnitude in Mandelbaum et al. 2005, figure 3. The factor of Σ_c^{-2} converts the shape noise in the denominator to a noise in $\Delta\Sigma$; it down-weights pairs that are close in redshift, so that we are weighting by the inverse variance of $\Delta\Sigma$.

There are several additional procedures that must be done when computing the signal (see Mandelbaum et al. 2005 for details). First, the signal computed around random points must be subtracted from the signal around real lenses to eliminate contributions from systematic shear. Second, the signal must be boosted, i.e., multiplied by $B(R) = n(R)/n_{\text{rand}}(R)$, the ratio of the weighted number density of sources around real lenses relative to the weighted number density of sources around random points in order to account for the dilution of the lensing signal due to sources that are physically associated with a lens, and therefore not lensed.

To determine errors on the lensing signal and boost factors, we divide the survey area into 200 bootstrap subregions and generate 500 bootstrap-resampled datasets.

The source galaxy catalogue used here was introduced and described in Reyes et al. (2012), which is an improved version of the catalogue from Mandelbaum et al. (2005). The full sample covers an area of 9243 deg^2 , containing over 39 million galaxies from SDSS DR8. For the lensing calculation in this work, we used a subset of that area that overlaps with the lens galaxy sample (around 8% of the parent galaxy sample was in areas without source galaxy shape measurements, so were excluded from the calculation).

The shape measurements utilise a method of PSF-correction known as re-Gaussianization (Hirata & Seljak 2003). Re-Gaussianization is a method based on the use of the moments of the image and of the PSF to correct for the effects of the PSF on the galaxy shapes. However, unlike many other moments-based corrections, it includes corrections for the non-Gaussianity of the galaxy profile (Bernstein & Jarvis 2002; Hirata & Seljak 2003) and of the PSF (to first order in the PSF non-Gaussianity). For more details, we refer the reader to § 4 and Appendices A & B of Reyes et al. (2012) and Mandelbaum et al. (2005).

3 SIMULATION AND HALO CATALOGS

The foundation of our mock galaxy catalogs is the Bolshoi N -body simulation (Klypin et al. 2011). With a force resolution of $\epsilon = 1 h^{-1}\text{kpc}$, the simulation solves for the evolution of 2048^3 collisionless particles in a ΛCDM cosmological model with $\Omega_m = 0.27$, $\Omega_\Lambda = 0.73$, $\Omega_b = 0.042$, $h = 0.7$, $\sigma_8 = 0.82$, and $n_s = 0.95$. The periodic box of Bolshoi has a side length of $250 h^{-1}\text{Mpc}$; each particle has mass of $m_p \simeq 1.9 \times 10^8 M_\odot$. The simulation was run with the Adaptive Refinement Tree Code (ART; Kravtsov et al. 1997; Gottloeber & Klypin 2008). Snapshots and halo catalogs are available at <http://www.multidark.org>. We refer the reader to Riebe et al. (2011) for additional information.

To construct our mocks, we use ROCKSTAR merger trees and halo catalogs (Behroozi

et al. 2013a,b), which are publicly available at <http://hipacc.ucsc.edu/Bolshoi/MergerTrees.html>. ROCKSTAR identifies and tracks halos in phase-space, and is capable of resolving Bolshoi halos and subhalos down to $V_{\max} \sim 55 \text{ km s}^{-1}$. Halo masses were calculated using spherical overdensities according to the redshift-dependent virial overdensity criterion of Bryan & Norman (1998).

4 MODEL

We use a two-phase algorithm to assign stellar mass and $g-r$ color to our halos and subhalos in the halo catalog. Our implementation is identical to that in Paper I, except with stellar mass M_* replacing r -band absolute magnitude. We sketch this algorithm in § 4.1 and § 4.2, and refer the reader to Paper I for further details. In § 4.3 we describe how the age matching technique is a special case of a more general class of CAM models, and provide an analytical formulation of CAM.

4.1 Stellar Mass Assignment

We use the abundance matching technique to assign stellar masses to halos and subhalos. This technique is widely used throughout the literature, and so we limit ourselves here to a brief sketch of the essential features.

A halo's maximum circular velocity is defined as $V_{\max} \equiv \text{Max} \left\{ \sqrt{GM(<r)/r} \right\}$, where $M(<r)$ is the mass interior to the halo-centric distance r . Abundance matching requires that the observed cumulative abundance of galaxies as a function of stellar mass, $N_g(>M_*)$, is equal to the cumulative abundance of (sub)halos with circular velocities larger than V_{\max} , $N_h(>V_{\max})$. This requirement uniquely determines a monotonic relationship between M_* and V_{\max} ; we use this monotonic relation to paint stellar masses onto every (sub)halo in the $z=0$ Bolshoi halo catalog.

To carry out the abundance matching, we use the halo property V_{peak} , the largest value of V_{\max} the halo ever attains throughout its assembly history (Reddick et al. 2012; Behroozi et al. 2013). We model stochasticity between stellar mass and V_{peak} in the exact same fashion described in detail in Appendix A of Hearin et al. (2012), which results in uniform scatter in stellar mass of $\sim 0.15 \text{ dex}$ at fixed V_{peak} , a level of scatter that is consistent with that found in a variety of other studies (More et al. 2009; Reddick et al. 2012; Hearin et al. 2012).

4.2 Color Assignment

After assigning stellar masses to mock galaxies, we proceed to the second phase of our algorithm, in which we assign $g-r$ colors. First, we bin the mock and SDSS galaxies by stellar mass, using ten logarithmically spaced bins spanning the range of both samples.³ The $g-r$ colors of the SDSS galaxies in each stellar mass bin empiri-

cally define the probability distribution $P_{\text{SDSS}}(g-r|M_*)$. For the N mock galaxies in each stellar mass bin, we randomly draw N times from $P_{\text{SDSS}}(g-r|M_*)$, rank-ordering each bin's draws, reddest first. We assign these colors to the mock galaxies in the corresponding stellar mass bin after first rank-ordering these N mock galaxies by the property z_{starve} (defined below), largest first.

After carrying out the above procedure in each stellar mass bin, the $g-r$ distribution of the mock galaxies is in exact agreement with the data, by construction. This agreement is illustrated in the top left and bottom panels of Fig. 1. Note that the rank-ordering has no impact on the agreement between the observed and mock color PDFs. The only effect of the rank-ordering is to introduce, at fixed stellar mass, a correlation between galaxy color and the epoch in a halo's MAH presumed to be linked to the stifling of star formation, z_{starve} .

Three characteristic epochs in the main progenitor history of a halo determine its z_{starve} value:

1. z_{char} : The first epoch at which halo mass exceeds a characteristic mass of $M_{\text{char}} = 10^{12} h^{-1} M_{\odot}$. For halos that never attain this mass, $z_{\text{char}} = 0$.

2. z_{acc} : For subhalos, this is the epoch after which the object always remains a subhalo. For host halos, $z_{\text{acc}} = 0$.

3. z_{form} : We follow Wechsler et al. (2002) in our definition of the formation epoch of a halo, using their halo concentration-based proxy for halo age⁴. This identifies the redshift at which the halo transitions from the fast-to-slow-accretion regime, and the circular velocity V_{\max} of the halo plateaus.

After computing each of these three characteristic epochs, we define the redshift of starvation:

$$z_{\text{starve}} \equiv \text{Max} \{ z_{\text{acc}}, z_{\text{char}}, z_{\text{form}} \}. \quad (5)$$

For details concerning how exactly to calculate z_{starve} from halo merger trees, we refer to the appendix of Paper I.

4.3 Analytical Formulation of CAM

Age matching admits a relatively simple analytical description that makes clear why we consider our model to be a specific case of a larger class of CAM models. We first consider the analytical formulation of traditional abundance matching to highlight this connection.

The basic outcome of the abundance matching prescription is to determine $P(M_*|V_{\max})$, the probability that a (sub)halo with circular velocity V_{\max} hosts a galaxy with stellar mass M_* . In the absence of scatter between V_{\max} and M_* ,⁵ abundance matching treats $P(M_*|V_{\max})$ as a delta function centered at the value $V_{\max}(M_*)$, the mean circular velocity of the halo of a galaxy with stellar mass M_* . To see how the map

³ We have performed a variety of explicit tests to verify that our results are not sensitive to our bin width.

⁴ We use the $z=0$ concentration for host halos, and the concentration at the time of infall for subhalos.

⁵ See Behroozi et al. (2010) for a discussion of the analytical formulation of abundance matching in the presence of scatter.

$V_{\max}(M_*)$ is determined analytically, let dn_h/dV_{\max} denote the abundance of dark matter (sub)halos as a function of V_{\max} , and dn_g/dM_* the observed stellar mass function (SMF). Then the cumulative abundances are given by

$$N_h(> V_{\max}) = \int_{V_{\max}}^{\infty} dV'_{\max} \frac{dn_h}{dV'_{\max}} \quad (6)$$

$$N_g(> M_*) = \int_{M_*}^{\infty} dM'_* \frac{dn_g}{dM'_*} \quad (7)$$

In the absence of scatter, traditional abundance matching assumes that M_* and V_{\max} are in perfect monotonic correspondence in such a way that the cumulative abundances agree at all stellar masses. For any value of V_{\max} , this can be accomplished analytically by simply finding the zero of the following function

$$F_{V_{\max}}(M_*) \equiv N_h(> V_{\max}) \times \frac{dV_{\max}}{dM_*} - N_g(> M_*), \quad (8)$$

where dV_{\max}/dM_* is the Jacobian of the map $V_{\max}(M_*)$.

In CAM, we seek to specify a more complicated probability distribution function (PDF), $P(M_*, c|V_{\max}, X_{\text{halo}})$, the probability that a galaxy of stellar mass M_* and color c resides in a halo with circular velocity V_{\max} and an additional halo property X_{halo} , where $X_{\text{halo}} = z_{\text{starve}}$ in the case of age matching. We begin by making the following assumption of separability:

$$P(M_*, c|V_{\max}, X_{\text{halo}}) = P(M_*|V_{\max}) \times P(c|V_{\max}, X_{\text{halo}}). \quad (9)$$

We compute the first factor on the right hand side of Eq. 9 by using traditional abundance matching to determine $V_{\max}(M_*)$ (and hence $P(M_*|V_{\max})$), so that we may piggyback on the well-known successes of this simple approach to galaxy-halo modeling. However, this is not a necessary feature of age matching; one may instead wish to use, for example, a conditional stellar mass function approach to paint stellar masses onto halos.

The second factor on the right hand side of Eq. 9 is related to $P(c|V_{\max})$ through simple parameter marginalization:

$$P(c|V_{\max}) = \int dX_{\text{halo}} P(c|V_{\max}, X_{\text{halo}}) P(X_{\text{halo}}|V_{\max}), \quad (10)$$

where $P(X_{\text{halo}}|V_{\max})$ is tabulated directly from the simulation.

The left hand side of Eq. 10 is related to the observed color distribution by the defining equation of age matching:

$$P(c|V_{\max}(M_*)) \frac{dV_{\max}}{dM_*} = P_{\text{DATA}}(c|M_*). \quad (11)$$

Putting the above pieces together, we have

$$P_{\text{DATA}}(c|M_*) \frac{dM_*}{dV_{\max}} = \int dX_{\text{halo}} P(X_{\text{halo}}|V_{\max}) \times P(c|V_{\max}, X_{\text{halo}}). \quad (12)$$

The left hand side of Eq. 12 is tabulated directly from the data; the first term in the integrand on the right hand side

of Eq. 12 is determined directly from the simulation. The quantity $P(c|V_{\max}, X_{\text{halo}})$ is the fundamental quantity we wish to determine. We do so in an exactly analogous fashion to standard abundance matching.

First we define the following two conditional cumulative abundances:

$$N_h(> X_{\text{halo}}|V_{\max}) = \int_{X_{\text{halo}}}^{\infty} dX'_{\text{halo}} \left(\frac{dn_h}{dX'_{\text{halo}}} \right) |_{V_{\max}}$$

$$N_g(> c|M_*) = \int_c^{\infty} dc' \left(\frac{dn_g}{dc'} \right) |_{M_*}, \quad (13)$$

where $(dn_h/dX'_{\text{halo}})|_{V_{\max}}$ is the abundance of halos with circular velocity V_{\max} as a function of X_{halo} , and $(dn_g/dc')|_{M_*}$ is the abundance of galaxies with stellar mass M_* as a function of color. In the absence of scatter, $P(c|V_{\max}, X_{\text{halo}})$ is simply a delta function centered at the map $c(V_{\max}, X_{\text{halo}})$, which is computed by finding the zero of

$$F_{V_{\max}, X_{\text{halo}}}(c) \equiv N_h(> X_{\text{halo}}|V_{\max}) \times \frac{dV_{\max}}{dM_*} - N_g(> c|M_*). \quad (14)$$

The technique described above is very general; in principle it can be applied any observable property of galaxies, and can be implemented with any halo property. Since the model we study in this paper uses $X_{\text{halo}} = z_{\text{starve}}$ as the second halo property, which is primarily driven by formation time, we refer to this particular implementation as age matching. We discuss other possible implementations and applications of the CAM formalism in § 7.

5 PREDICTIONS

We evaluate the success of our model by computing statistics of our mock galaxy sample in a directly analogous fashion to the manner in which the corresponding statistics are computed in observational data. We describe our technique for computing projected clustering of mock galaxies in § 5.1, the mock galaxy-galaxy lensing in § 5.2, and mock galaxy group statistics in § 5.3.

5.1 Projected Clustering of Mock Galaxies

The projected clustering of galaxies $w_p(r_p)$ quantifies the probability in excess of random that a pair of galaxies in a sample will have line-of-sight separation less than π_{\max} and be found at projected separation r_p . Suppose that N_g galaxies are randomly distributed throughout a cubical box of side length L_{box} . Then in a randomly placed cylindrical annulus of length π_{\max} , and with inner and outer radii r_{\min} and r_{\max} , respectively, the expected number of galaxy pairs is

$$N_{p,\text{ran}} = \frac{1}{2} N_g (N_g - 1) (\pi r_{\max}^2 - \pi r_{\min}^2) \pi_{\max} / L_{\text{box}}^3.$$

By directly computing N_p , the actual number of galaxy pairs in our mock that satisfy this line-of-sight and pro-

jected distance criterion,⁶ we compute $1 + w_p(r_p) = N_p/N_{p,\text{ran}}$. We use $\pi_{\text{max}} = 40 \ h^{-1}\text{Mpc}$ to be consistent with the measurements made for our observational samples.⁷ We estimate errors on w_p by jackknifing the octants of the simulation box.

5.2 Mock Galaxy-Galaxy Lensing

We compute the mock galaxy-galaxy lensing signal $\Delta\Sigma$ from the particle data as follows. For every galaxy in each mock, we compute the two-dimensional projected mass density profile in 25 logarithmic bins in radius from 0.2 to 2.0 $h^{-1}\text{Mpc}$. The density from 0 to 0.2 $h^{-1}\text{Mpc}$ is recorded as well for computing $\Delta\Sigma$ later. The two-dimensional mass profile is computed from a projection over a length of 100 $h^{-1}\text{Mpc}$ along the z -axis of the simulation box (i.e., from 50 $h^{-1}\text{Mpc}$ behind the galaxy to 50 $h^{-1}\text{Mpc}$ in front of the galaxy). With the two-dimensional density profiles, we then compute $\Delta\Sigma$ around each galaxy for the i th bin as

$$\Delta\Sigma_i = \frac{1}{\pi R_{i-1,\text{max}}^2} \sum_{n=0}^{i-1} \Sigma_n A_n - \Sigma_i, \quad (15)$$

where Σ_i is the surface density of mass in the i th bin and $A_i = \pi(R_{i,\text{max}}^2 - R_{i,\text{min}}^2)$ is the area of each annulus. Here $R_{\text{min},i}$ and $R_{\text{max},i}$ are the minimum and maximum radius of the i th annulus. The errors on $\Delta\Sigma$ are computed via 27 jackknife regions over the simulation volume.

The procedure for computing $\Delta\Sigma$ defined above is approximate for several reasons. First, in the limit that each galaxy is in a thin lens at the galaxy's redshift in both the simulation and the data, the procedure defined above is an exact match to how $\Delta\Sigma$ is computed from observational data. However, in reality, a given galaxy is not in a thin lens, but is instead in an extended mass distribution. Thus along the projected line-of-sight, the lensing kernel will supply an additional line-of-sight dependent weight. The exact form of this weight depends in detail on the redshift distributions of the lenses and sources in the observational samples. Given that the galaxy-matter correlation function falls off quickly as a function of radius, we have chosen to completely neglect this effect. Second, the projection along the line-of-sight should be done over a full light cone. However, again because the galaxy-matter correlation function falls off quickly as a function of radius, we have fixed the line-of-sight projection length to 100 $h^{-1}\text{Mpc}$ (see also Leauthaud et al. 2011). Finally, note also that the box length for Bolshoi is only 250 $h^{-1}\text{Mpc}$ and that the simulation volume is periodic. Thus particles in the volume can be separated by at most half the box length, 125 $h^{-1}\text{Mpc}$, and so we can project the mass distribution only over at most this

length. Thus our chosen projection length is a compromise between the need to make it as large as possible in order to match the data accurately and the constraints of the given simulation volume.

5.3 Group Identification of Mock Galaxies

To parse the $M_*^{9.8}$ mock galaxies into groups, we use the simulation z -coordinate to place mock galaxies into redshift-space, convert $x - y$ coordinates into RA and DEC, and then apply the same group-finding algorithm on the mock galaxies as we applied on the SDSS galaxy sample. In this way, our mock galaxy group sample is subject to the same systematic errors as our SDSS groups. For further details concerning group-finding in a mock, we refer the reader to Hearin et al. (2012).

6 RESULTS

In this section, we present our main results. In § 6.1 we show that our age matching model predicts the correct relative colors of central and satellite galaxies. Then in § 6.2 we demonstrate the accuracy of our base $M_*^{9.8}$ SDSS mock catalog at reproducing new SDSS measurements of the projected galaxy 2PCF as a function of stellar mass, explicitly showing that our mock catalog naturally inherits the successes of traditional abundance matching. We then compare the age matching predictions to SDSS measurements of the 2PCF split into red and blue samples. We also investigate the success of our age matching model with new SDSS galaxy-galaxy lensing measurements in § 6.3, a statistic which was not explored in Paper I. As is done for clustering, we consider the lensing signal, $\Delta\Sigma$, as a function of stellar mass, and then for distinct red and blue subsamples. We also test the success of our model against statistics measured from the $M_*^{9.8}$ SDSS group catalog in § 6.4. Finally, in § 6.5 we dissect z_{starve} to examine exactly how halo mass assembly is linked to shaping the colors of galaxies within age matching. This includes a discussion of alternative models that have been tested and the power of the more general CAM formalism.

6.1 Central and Satellite Colors

As discussed in § 4.2, our model correctly reproduces the color distribution $P_{\text{SDSS}}(c|M_*)$ by construction as seen in the top left panel and bottom row of Fig. 1. However, the information about satellite/central designation does not inform the colors we assign to the galaxies. Specifically, our color assignment only uses the property z_{starve} and $P_{\text{SDSS}}(c|M_*)$ to assign colors to the mock galaxies but does not distinguish between centrals and satellites. Thus, by no means is it guaranteed that our color PDFs will be correctly predicted when conditioned on some other galaxy property beyond stellar mass. The top middle and right panels of Fig. 1 clearly demonstrate the successful prediction of age matching for the separate color PDFs of central and satellite galaxies. In our model, *central and satellite galaxies of the same stellar mass have different color distributions simply because host halos and subhalos have different MAHs.*

⁶ We employ the *distant observer approximation*, using the z -direction in the simulation to compute line-of-sight distances, and the $x - y$ plane to compute projected distances.

⁷ In computing the actual pair counts in the simulation, we first place the galaxies into redshift space, though we find that this has a negligible effect on the projected correlation function.

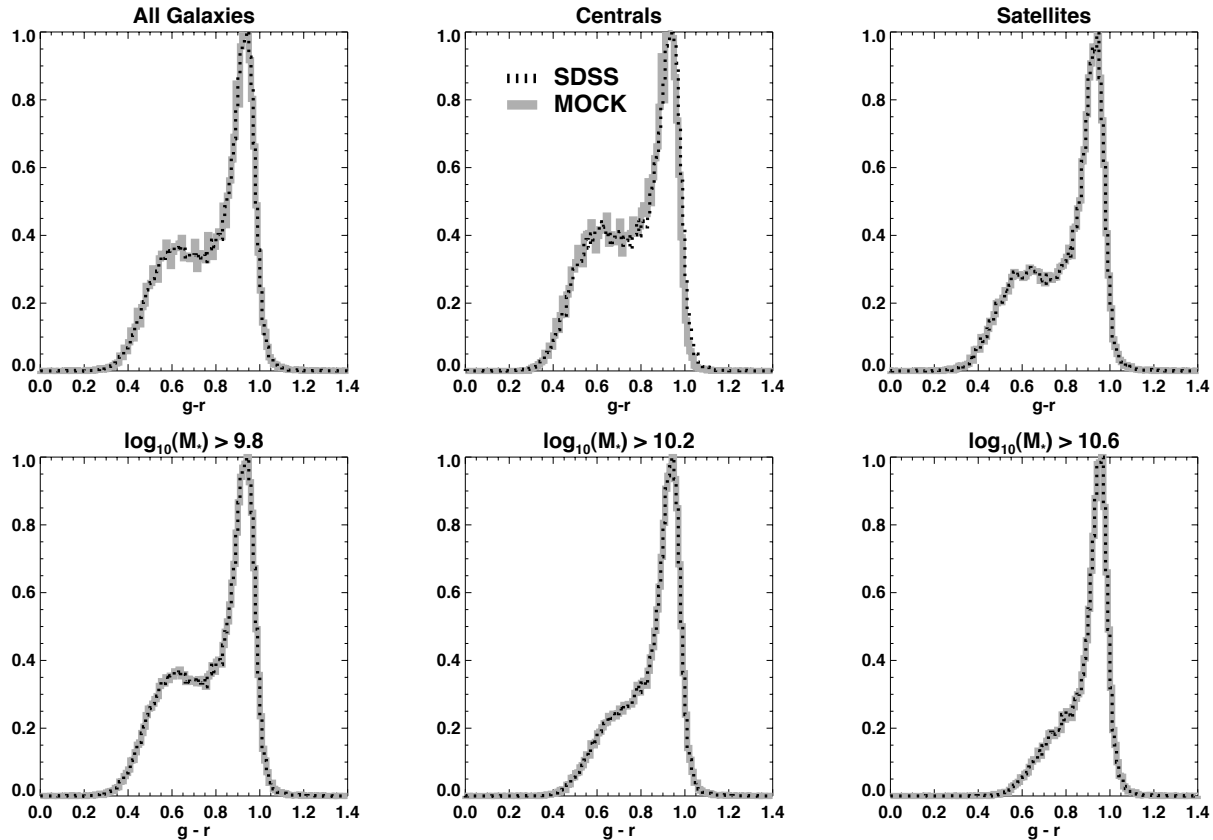


Figure 1. Galaxy color probability distribution functions (PDFs) from our mock catalog as compared to those measured in the SDSS galaxy catalogs. The $g-r$ color PDFs of our mock galaxies are in exact agreement with the data (black dotted histograms) for the all galaxy sample (top left panel) and all three stellar mass threshold samples (bottom row), by construction. Our color assignment to galaxies is blind to central/satellite designation, thus the PDFs measured from the $M_{*}^{9.8}$ group catalog, as seen in the center and right panels of the top row, demonstrate the highly successful *predictions* of age matching.

6.2 Galaxy Clustering

In the top row of Fig. 2, black solid curves with gray error bands (see section § 5.1 for a discussion of error estimates) show the projected 2PCF measured from our mock catalog for all galaxies predicated on traditional abundance matching. The excellent agreement with the SDSS data points (filled black circles) illustrates that galaxies have been properly assigned to halos as a function of stellar mass. However, notice there is a slight under-prediction from abundance matching on small scales for the $M_{*}^{10.2}$ sample.

We now turn to the bottom row of Fig. 2 to investigate the success of age matching at predicting color-dependent clustering. Red and blue filled circles in all panels represent the red and blue galaxy populations from SDSS, respectively. Red and blue solid curves are the age matching model predictions. The $M_{*}^{9.8}$ and $M_{*}^{10.6}$ predictions for the color-dependent clustering are in excellent agreement with the data at all scales. However, as noted above, there is a slight under-prediction of abundance matching on small scales ($r_p \lesssim 500h^{-1}\text{kpc}$) for the $M_{*}^{10.2}$ sample and this propagates through to the color split (bottom, center panel), though the relative color

split of the model agrees well with what is dictated by the data.

We emphasize that our age matching model has required no parameter fitting to achieve the agreement between the predicted and measured color-dependent clustering. Our algorithm for color assignment has no explicit dependence on halo position; the clustering signal in our mock simply emerges as a *prediction* of age matching. The success of our model is compelling given the simplicity of age matching, and the more general CAM formalism.

6.3 Galaxy-Galaxy Lensing

While the 2PCF encodes rich information about the galaxy-halo connection, measurements of galaxy-galaxy lensing have been shown to break degeneracies between galaxy-halo parameters that are present when model constraints are derived from clustering measurements alone (e.g., More et al. 2013). To that end, in Fig. 3 we compare our model prediction to new measurements of the stellar mass- and color-dependent galaxy-galaxy lensing signal, $\Delta\Sigma$. As was the case for the 2PCF comparison, we accurately predict $\Delta\Sigma$ at the abundance matching level

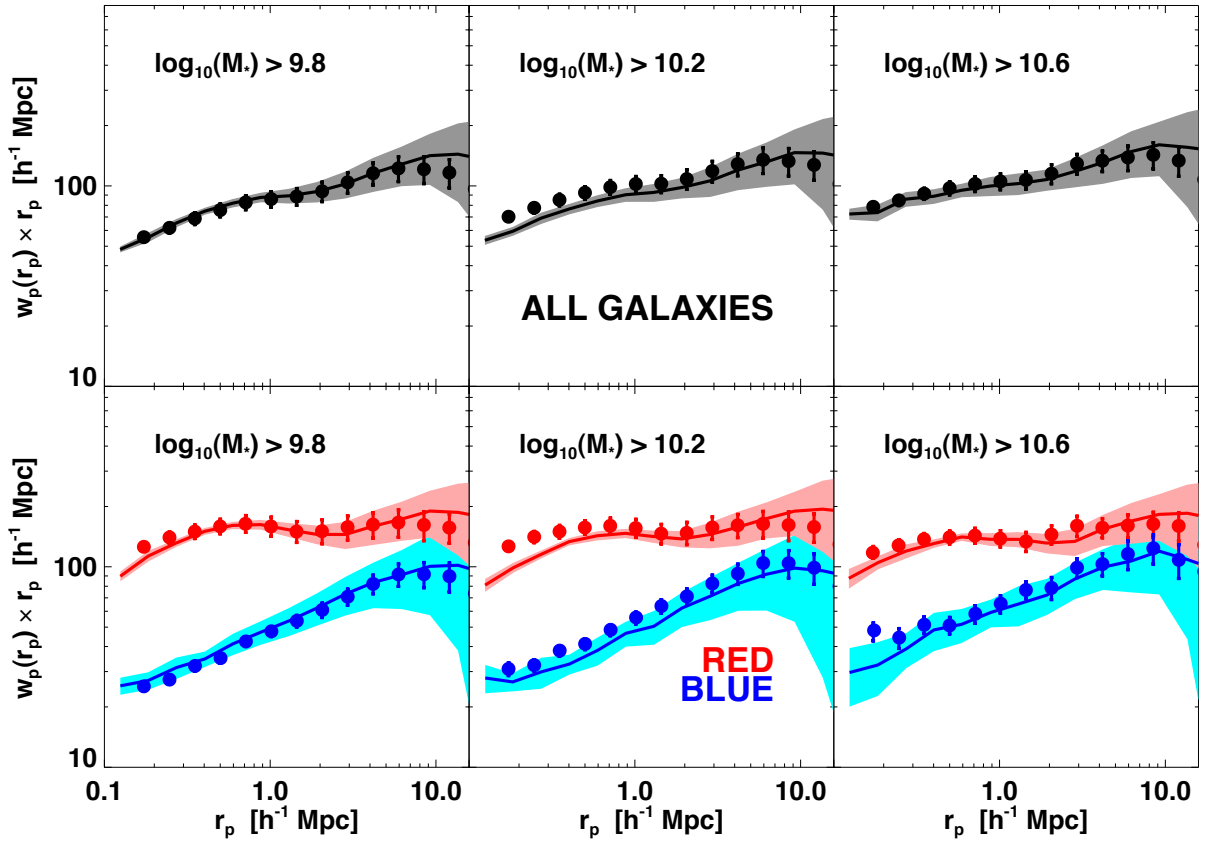


Figure 2. Stellar mass- and color-dependent clustering as predicted by our age matching formalism. *Top Row:* The projected correlation function (multiplied by r_p) predicted by our model (black solid curves) as compared to the clustering of three SDSS stellar mass threshold samples: $\log_{10}(M_*) > [9.8, 10.2, 10.6]$. *Bottom Row:* Correlation functions split by color for red (blue) mock galaxies shown with red (blue) solid curves. Red (blue) points show the clustering of red (blue) SDSS galaxies. Solid bands in each panel show the error in our model prediction as described § 5.1. The $\log_{10}(M_*) > 9.8$ and $\log_{10}(M_*) > 10.6$ predictions for the color-dependent clustering are in excellent agreement with the data at all scales. The slight under-prediction of abundance matching on small scales for the $\log_{10}(M_*) > 10.2$ sample (top, center panel) propagates through to the color split (bottom, center panel), though the relative color split is captured by the model.

(black solid curves versus SDSS solid black data points in the top row), though the amplitude of the model prediction appears slightly boosted relative to the data for all three stellar mass thresholds. Red and blue filled circles in all panels represent the red and blue SDSS galaxy populations, respectively, while red and blue solid curves are the model predictions according to age matching. The separation in $\Delta\Sigma$ between red and blue samples is predicted reasonably well, excepting only blue samples on small scales, where measurement errors become large.

6.4 Galaxy Group Environment

In addition to $w_p(r_p)$ and $\Delta\Sigma$, we employ a group-finder to test how well our model predicts the scaling of central and satellite color with host halo mass. As our proxy for halo mass we use M_*^{BCG} , the stellar mass of the group’s central galaxy. In Fig. 4, we show the mean $g - r$ color of group galaxies as a function of M_*^{BCG} . We show the results for central galaxies and satellites from left to right, respectively. The dashed line is the mean $g - r$ color of

the mock galaxies in a given M_*^{BCG} bin. The solid gray region shows Poisson errors on the mean color in each bin.

There is excellent agreement between mock and observed satellite galaxy color. This is also true for central galaxies excepting some slight tension at the low M_*^{BCG} end. Again, we emphasize that we have not tuned any parameters in our model. The successful prediction for central and satellite colors naturally emerges from the age distribution matching formalism. Specifically, at fixed stellar mass, the colors of our mock galaxies are drawn from the same color PDF, $P_{\text{SDSS}}(c|M_*)$, regardless of subhalo or host halo designation. Moreover, our color assignment algorithm takes no explicit account of subhalo or host halo mass. Therefore, our model’s correct prediction for the environmental-dependence of satellite and central galaxy colors arises purely due to the environmental dependence of V_{max} and z_{starve} of dark matter halos and subhalos.

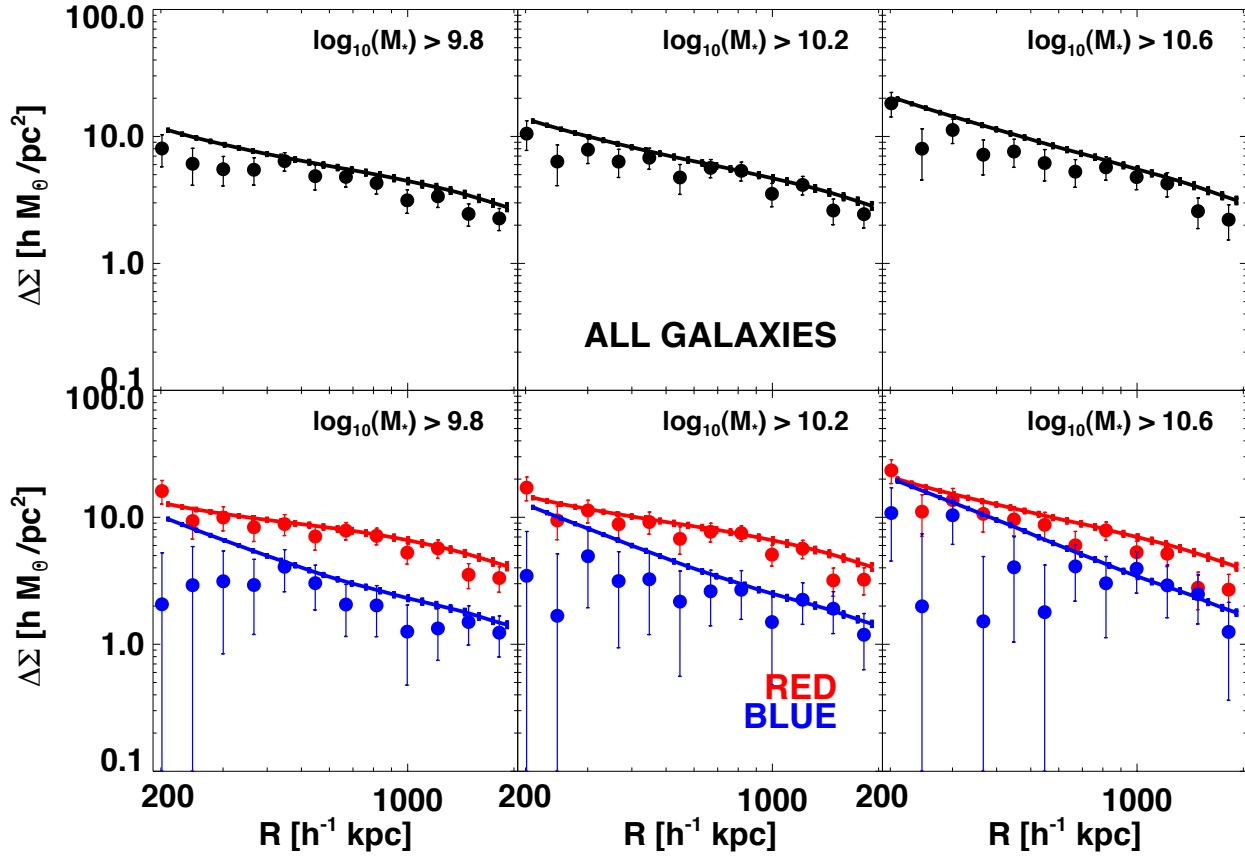


Figure 3. $\Delta\Sigma$ as a function of stellar mass and color. As was shown for the projected clustering in Fig. 2, the top row is the abundance matching result for all galaxies and the bottom row shows the predicted color split from our age matching model (red and blue solid curves) as compared to new SDSS galaxy-galaxy lensing measurements. Derived errors for the data and the model are described in § 2.4 & § 5.2, respectively.

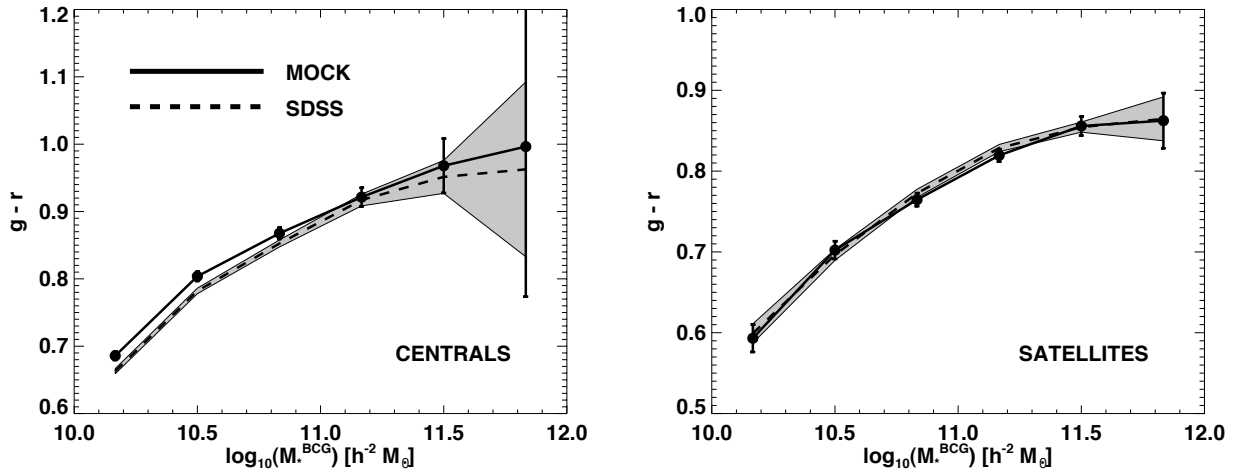


Figure 4. Mean $g-r$ color as a function of stellar mass of the brightest central galaxy, M_*^{BCG} , for SDSS galaxies (black filled circles) and the prediction from our mock catalog (dashed curves). Solid gray bands are the errors computed as the dispersion over 1000 bootstrap realizations of the galaxy sample. Results for central galaxies are shown in the left panel and satellite galaxies in the right.

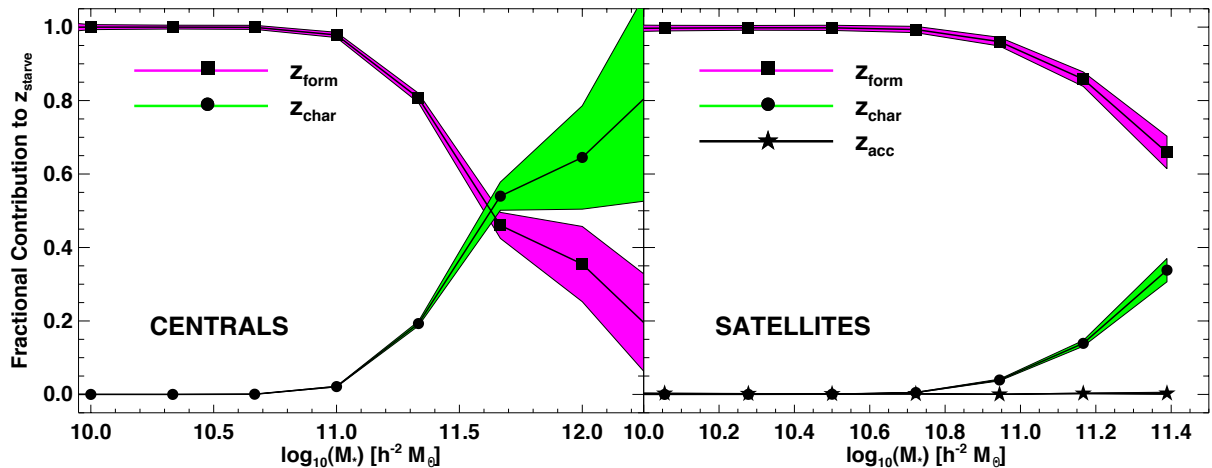


Figure 5. The fractional contribution to z_{starve} from the three characteristic epochs in the mass accretion history of halos that constitute age matching. Results for central and satellite galaxies are shown in the left and right panels, respectively. While more and more galaxies naturally receive a z_{starve} value based on z_{char} as we go to higher central and satellite stellar masses, z_{acc} makes almost no contribution at any stellar mass for satellites. As seen in Fig. 6 and described in § 6.5 this is due to the strong correlation between the z_{form} and z_{acc} .

6.5 Fractional Contributions to z_{starve}

As laid out in § 4.2, a halo’s z_{starve} value is determined by whichever of the following three events happens first in its MAH: (1) the epoch a halo accretes onto a larger halo, z_{acc} (this of course only pertains to satellite galaxies), (2) the epoch a halo reaches a characteristic mass of $10^{12} h^{-1} M_{\odot}$, z_{char} , and (3) the epoch a halo transitions from the fast- to slow-accretion regime, z_{form} . Figure 5 shows the fractional contribution to z_{starve} from z_{form} (star symbols), z_{char} (filled circles) and z_{acc} (triangles) as a function of galaxy stellar mass. Gray bands are the Poisson errors for a given stellar mass bin.

First consider central galaxies in the left panel; z_{form} (solid magenta curve) dominates the fractional contribution at $\sim 100\%$ up to $\log_{10}(M_*) = 11.0$ (roughly L^* galaxies), and precipitously declines to $\sim 50\%$ at $\log_{10}(M_*) = 11.5$. The halo property z_{char} was originally introduced into age matching because older halos receive redder colors, and so without z_{char} , high mass galaxies (e.g., BCGs residing in clusters) would be assigned colors that are too blue since their halos are still forming today. As discussed in Paper I, our phenomenological model forms no particular hypothesis for the particular physical mechanism(s) that influence star formation within massive halos. We simply posit that there exists a characteristic halo mass above which star formation becomes inefficient. Physically, this presumption is well-motivated by hydrodynamical simulation results that implement AGN feedback, which can have a dramatic effect on star formation (Shankar et al. 2006; Teyssier et al. 2011; Martizzi et al. 2012)⁸. We have considered a form of the model in which z_{char} is neglected, and for stellar mass-

based galaxy samples we find that the effects on all of the galaxy statistics are minimal. We also considered a larger 2PCF stellar mass threshold $\log_{10}(M_*) > 11.0$, and while the color split became more pronounced with the inclusion z_{char} in the model, sample variance errors in Bolshoi were too large to quantitatively distinguish between models with and without z_{char} . However, we note that z_{char} was crucial for accurately predicting the brightest 2PCF luminosity bin in Paper I.

We see similar trends to the above for the satellite galaxies plotted in the right panel. Due to the rarity of massive objects, combined with the effects of tidal mass loss, satellite galaxies rarely achieve halo masses large enough for z_{char} to make an appreciable contribution to z_{starve} ($\sim 30\%$ at maximum).

The most dramatic result of this figure is the negligible contribution from z_{acc} , which is $\sim 0.1\%$ at all stellar masses. While striking, this cannot be directly interpreted as a lack of importance of post-accretion physics on shaping the colors of satellite galaxies because the accretion time and formation time of subhalos are correlated. This correlation can be directly seen in Fig. 6, in which we plot the lookback time to the epoch a subhalo is formed against the lookback time at which it is accreted. We show the mean t_{form} in bins of t_{acc} for satellites in several different bins of stellar mass, with the gray band illustrating the Poisson error on the mean for the smallest mass sample. Figure 6 demonstrates that the subhalo properties z_{acc} and z_{form} are correlated with high statistical significance.⁹ Thus, even though neglecting z_{acc} in our model does not affect our predictions, correlations between satellite quenching and accretion time nonetheless emerge from our model due to the connection between

⁸ See also Fang et al. (2013) for an observational investigation of bulge-driven quenching.

⁹ Note that although the *mean* trend is strong, there is roughly $\sim 0.5\text{Gyr}$ of scatter in t_{form} at fixed t_{acc} .

the epoch of accretion and the epoch of formation. We explore this point in detail in a follow-up paper focusing squarely on satellite quenching in our model.

We have chosen to maintain the exact formalism laid out in Paper I, with $z_{\text{starve}} \equiv \text{Max}\{z_{\text{acc}}, z_{\text{char}}, z_{\text{form}}\}$. However, we note that in light of the above discussion, we have tested a simple model with $z_{\text{starve}} = z_{\text{form}}$ and find that it performs on par with the more complicated model of Paper I. We have also considered alternative proxies for halo age beyond z_{form} that arise often in the literature, such as the redshift a halo attains 4% of its present day mass, $z_{4\%}$, or the redshift it attains half of its present day mass, $z_{1/2}$. A model based on $z_{4\%}$ works just as well as our model, which should not be surprising since the 4% criterion has already been shown to give a very similar estimate of the epoch a halo transitions from the fast- to slow-accretion regime (Zhao et al. 2009). While a model based on $z_{1/2}$ correctly predicts the general trends of all of the galaxy statistics we tested, the results are in significantly worse quantitative agreement. This is interesting in light of recent results on *pseudo-evolution* that imply $z_{1/2}$ is a poorly motivated physical proxy for halo age: by the time a typical Milky Way halo attains half of its present day mass, its accretion rate is almost entirely due to the changing background mean density, to which we see no plausible connection to galaxy evolution (Diemer et al. 2013). Motivated by the prevalence of alternative approaches to the galaxy-halo connection that rely exclusively on host halo mass, we also considered a model that rank-ordered on the present day mass of the host halo instead of z_{starve} ; this model made clustering predictions that are grossly discrepant with the data.

The flexibility of the CAM formalism makes exploration of alternative formulations completely straightforward. In the end, z_{starve} may not be the fundamental halo variable that correlates with color; all that can be said from the diverse success of our model is that, whatever this truly fundamental halo property is, it must correlate strongly with z_{starve} . We relegate a more exhaustive exploration of alternative CAM implementations as a task for future work, and comment further on this effort in § 7.

7 DISCUSSION

7.1 Physical Motivation of Age Matching

The physical picture suggested by the myriad successes of abundance matching is that the depth of a halo’s gravitational potential well (V_{max}) is the single most important quantity in the evolution of a galaxy. The use of z_{form} in age matching takes this picture seriously. The potential well of a halo is primarily built during the early stage of fast accretion. After the fast-to-slow accretion transition, mass accretes onto the halo from the outside-in, and halo mass can substantially increase without changing V_{max} (Wechsler et al. 2002; Zhao et al. 2003). Even on an individual halo basis, this fact about structure growth in CDM is readily apparent by visual inspection of the assembly history of dark matter halos. Thus the use of z_{form} in age matching is physically motivated by the expecta-

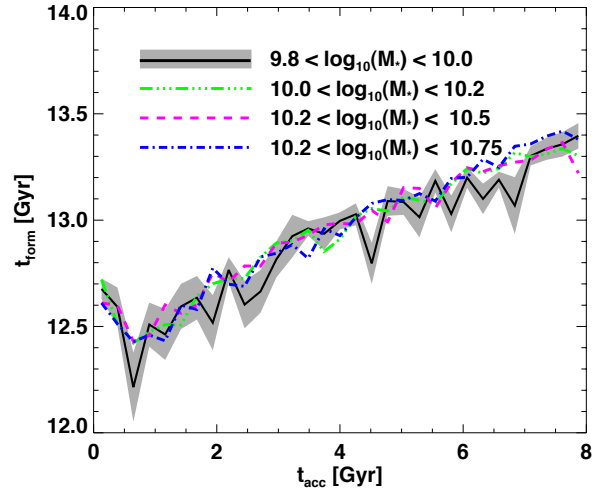


Figure 6. Plot of the lookback time to the epoch a subhalo is formed, t_{form} , versus the lookback time at which the subhalo is accreted, t_{acc} . Different curves show results for different bins of satellite stellar mass, with the gray band showing Poisson errors for the lowest mass sample. While Fig. 5 showed the negligible contribution of z_{acc} in our model, this figure demonstrates that satellite quenching in our model is nonetheless connected to accretion time due to the $t_{\text{form}}-t_{\text{acc}}$ correlation in CDM structure formation.

tion that stellar mass build-up slows down once the depth of the central potential is in place, so that galaxies with older stellar populations will tend to be found in halos with potential wells that formed earlier.

7.2 The Simplicity of CAM

The successes of CAM are particularly interesting in the context of other approaches to modeling the galaxy-halo connection. First consider the commonly-used Halo Occupation Distribution (HOD: e.g., Peacock & Smith 2000; Seljak 2000; Scoccimarro et al. 2001; Berlind & Weinberg 2002; Cooray & Sheth 2002; Zheng et al. 2007) formalism (or the closely related conditional luminosity function, Yang et al. CLF: e.g., 2003; van den Bosch et al. CLF: e.g., 2007). The central quantity in the HOD is $P(N|M)$, the probability that a (host) halo of mass M hosts N galaxies of some type. The HOD formalism was developed over ten years ago, and there are many noteworthy successes of this approach to modeling galaxy color and/or star formation rate (e.g., Skibba & Sheth 2009; Zehavi et al. 2011).

In one respect, the HOD approach is simpler than ours: in the HOD, host halo mass is the only halo property that governs galaxy occupation statistics, whereas CAM models treat halos as objects with two properties (in the case of age matching, V_{max} and z_{starve}). On the other hand, HOD models typically require fitting for a comparatively large number of free parameters in order to model the color dependence of the spatial distribution of galaxies. As an example, consider the HOD model explored in Zehavi et al. (2011). For every color-selected

luminosity-threshold sample, this model requires fitting for five free parameters in a maximum likelihood analysis. Thus in order to model the clustering at three different thresholds for both red and blue galaxy samples, this approach requires fitting for a total of 30 free parameters, since each time the sample changes, new fits are required.

As another example, consider the HOD model employed in Tinker et al. (2013). Using a standard set of parameters for the HOD together with parameters describing the stellar-to-halo mass map $M_*(M_h)$, active and passive galaxy populations are modeled separately and fit to the observed stellar mass function $\Phi(M_*)$, angular clustering $w(\theta)$, and galaxy-galaxy lensing signal $\Delta\Sigma(R)$. This approach to the galaxy-halo model requires 27 free parameters at each redshift slice.

Semi-analytic models (SAMs) are an alternative to the phenomenological HOD- and CLF-type modeling. The distinct advantage of the SAM approach is that these models have the potential to yield constraints on the actual physical mechanisms responsible for galaxy evolution, since SAM models ostensibly parametrize the litany of baryonic processes that impact star formation and quenching. However, SAMs typically require a large number of finely tuned parameters to describe dynamical evolution of subhalos and the vast baryonic processes of galaxy formation (White & Frenk 1991; Kauffmann et al. 1999; Cole et al. 1994; Somerville & Primack 1999; De Lucia & Blaizot 2007; Guo et al. 2011). At present, there is no consensus in the literature on the correct SAM formulation, since quantitative comparisons between different models are difficult to conduct due to the inherent complexity of this approach.

By contrast, in our age matching implementation of CAM, we only require three free parameters: (1) scatter σ in the relation between V_{\max} and M_* , (2) the logarithmic slope S defining the transition from the fast-to-slow accretion regime of halo growth, and (3) the characteristic halo mass M_{char} where star formation becomes inefficient (recall that z_{acc} proved unnecessary). Once these three parameters are fixed, the full continuous distribution of colors (rather than a binary red/blue designation) is predicted for *all* stellar mass thresholds, since we implicitly use the color PDF directly from the data. Moreover, the exact same parameters work equally well for either stellar mass- or luminosity-threshold samples; as we will show in a companion paper to this one, the same holds true when using CAM to predict star formation rates rather than color. In this sense, our assumption that old halos host old galaxies results in a dramatically simpler model than conventional implementations of the HOD.

Though this simplification is tantalizing, it remains to be seen whether the model we have presented in this paper passes a χ^2 goodness-of-fit criterion for the projected clustering and galaxy-galaxy lensing signals in SDSS. However, we have not yet fit for our three parameters in a maximum likelihood analysis. We have simply chosen appropriate values from the literature and kept these fixed throughout this paper. Given how successful our model has proven to be without varying this small number of parameters, we consider it plausible that we will be able to achieve a good fit to the data once we conduct a Monte Carlo Markov Chain exploration of the

CAM parameter space. We consider this effort beyond the scope of the present work, though we intend to conduct this analysis in future work, both at low- and high-redshift.

7.3 Application to Star Formation Measurements

Though $g - r$ color is generally a good indicator of ongoing star formation in a galaxy, the correspondence is only approximate. For instance, star-forming galaxies can often appear red due to the presence of gas and dust (Maller et al. 2009; Masters et al. 2010; Wetzel et al. 2012). Additionally, the timescales relevant to, for example, $H\alpha$ indicators of star formation rates (SFR) are significantly shorter than timescales impacting $g - r$ color, and so it is reasonable to be skeptical that age matching will fail when connecting present day star formation rate to z_{starve} , since this halo property typically occurs in the very distant past. We show in a companion paper that this is not the case: the SFR predictions of our age matching implementation of CAM are equally successful as the predictions we show here. Thus a model with just three parameters, with no change to their values, correctly connects dark matter halos to galaxies of a given stellar mass, r-band luminosity, g-band luminosity, and SFR.

7.4 Assembly Bias Degeneracies

One important step in the development of CAM modeling will be to develop a better understanding of the degeneracies between CAM and the HOD. Evidently, both classes of models can effectively describe the color-dependence of the stellar mass function, two-point clustering, and galaxy-galaxy lensing signal, yet these models are predicated upon markedly different assumptions. In the HOD, knowledge of halo mass is sufficient to statistically characterize *all* properties of the galaxies populating a halo; in CAM, galaxy color correlates strongly with halo age at fixed halo mass; clearly, these are mutually incompatible assumptions. We briefly note here that models based only on host halo mass are unable even in principle to reproduce *galactic conformity*: the observation that, at fixed host mass, group systems with a blue central tend to have a bluer satellite population, and conversely for red centrals and satellites (Weinmann et al. 2006). This is a natural feature of age matching, since host halos and subhalos collapse from and co-evolve in the same overdense patch of the cosmic density field. We explore this fully in a future paper.

The dependence of galaxy occupation statistics upon some halo property besides mass generically goes by the name of *assembly bias*; Zentner et al. (in prep.) recently completed a first step towards understanding the degeneracies between HOD parameters and the assembly bias predicted by CAM-type models; in light of the simultaneous success of these very different approaches to galaxy-halo modeling, we consider a comprehensive effort to theoretically model and observationally constrain assembly

bias to be necessary in order to truly understand the connection between galaxies and dark matter halos.

7.5 Future Work

Even within the CAM framework there exists degeneracies between different implementations of the formalism. In § 6 we provide examples of how different definitions of z_{starve} can produce models of comparable success to our fiducial model. For example, age matching models that either account for or entirely ignore the post-accretion history of satellite galaxies make nearly identical predictions. This suggests that too much emphasis may have been placed on the role of post-accretion physics in satellite quenching. However, since z_{form} and z_{acc} are correlated, the success of models which do not include z_{acc} cannot be directly interpreted as evidence ruling out contributions to satellite quenching from intra-host processes.

Additionally, as we showed in Fig. 2 the influence of M_{char} only becomes significant for stellar masses that contribute minimally to the clustering in any of our samples. Thus the mass range of our sample apparently does not require invoking a cutoff in star formation efficiency, as discussed in § 6. In the interest of continuity with Paper I we have made no alterations to our definition of z_{starve} , though we will return to this issue in follow up work in which we explore more exhaustively the variety of different CAM implementations

The model studied in Masaki et al. (2013) is in essence a CAM model in which the conditional abundance is performed with halo central density rather than z_{starve} . It is not particularly surprising that both models are effective, because in age matching z_{starve} is primarily governed by halo concentration, which is of course strongly correlated with central density. On the one hand, our age matching model is physically motivated by the expectation that older halos tend to host galaxies with older stellar populations, while we see no plausible, comparably direct physical interpretation of the central density-based model. On the other hand, the simultaneous success of z_{starve} - and central density-based CAM models implies that caution is required before *any* particular implementation of CAM can be considered to be truly fundamental.

Despite these systematic uncertainties, what is quite clear from our results is that the CAM formalism provides a framework for the galaxy-halo connection that makes remarkably accurate predictions for a rich variety of observational data. We consider the preliminary success of this framework to be an extremely promising indication that the cosmic history of star formation in galaxies admits a simple, elegant theoretical description.

8 SUMMARY

We conclude by summarizing our primary results and conclusions:

1. We have made new DR7 SDSS measurements of the projected two-point correlation function, and galaxy-

galaxy lensing signal, as a function of stellar mass and $g-r$ color. Our measurements appear in Tables 1-6.

2. We use these new measurements to test the age matching formalism introduced in Hearin & Watson (2013) (Paper I), finding in all cases that our model performs quite well; the level of agreement is particularly remarkable considering the simplicity of the model, and that we have made no alternations to the values of the model parameters used in Paper I.

3. Additionally, we employ a galaxy group-finder to demonstrate that our model correctly predicts the colors of central and satellite galaxies. Indeed, the scaling of satellite galaxy colors with host halo mass is in essentially perfect agreement with SDSS data.

4. We present a very general formalism for modeling the galaxy-halo connection called Conditional Abundance Matching (CAM), of which age matching is a specific example. This flexible theoretical framework permits direct investigation of correlations between *any* galaxy property and *any* halo property.

5. We make publicly available a mock galaxy catalog constructed from our model at <http://logrus.uchicago.edu/~aphearin>.

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Table 1. SDSS PROJECTED CORRELATION FUNCTION MEASUREMENTS: ALL GALAXIES. The first column is the the mean radii of galaxies in each logarithmic bin in units of h^{-1} Mpc. Additional columns show the projected correlation function, $w_p(r_p)$, for three stellar mass, volume-limited threshold samples. The diagonal terms of the error covariance matrix are given in the parenthesis.

r_p	9.8	10.2	10.6
0.122	403.78 (18.80)	521.56 (25.91)	646.61 (32.25)
0.173	320.76 (15.07)	405.55 (19.47)	454.60 (24.62)
0.247	250.04 (14.57)	314.75 (18.65)	342.78 (19.72)
0.351	195.97 (13.40)	242.73 (16.24)	260.54 (16.80)
0.500	151.47 (11.28)	184.98 (13.38)	195.04 (14.68)
0.712	116.21 (9.41)	138.60 (11.13)	143.84 (12.16)
1.014	84.82 (7.57)	100.96 (9.10)	104.03 (9.52)
1.445	61.24 (5.95)	71.08 (6.97)	74.22 (7.36)
2.058	45.65 (5.09)	52.60 (5.91)	55.91 (6.11)
2.933	35.51 (4.15)	40.45 (4.80)	44.06 (4.96)
4.175	27.69 (3.49)	30.78 (3.87)	32.02 (3.78)
5.942	20.58 (2.91)	22.73 (3.33)	23.34 (3.28)
8.464	14.31 (2.19)	15.71 (2.46)	16.90 (2.54)
12.048	9.67 (1.56)	10.57 (1.72)	11.10 (1.83)
17.158	5.63 (1.28)	5.96 (1.41)	6.27 (1.55)

Table 2. SDSS PROJECTED CORRELATION FUNCTION MEASUREMENTS: BLUE GALAXIES. Same as Table 1, but for the blue galaxy samples.

r_p	9.8	10.2	10.6
0.121	172.54 (9.75)	207.29 (16.17)	310.74 (42.11)
0.173	146.40 (7.96)	178.88 (13.34)	275.17 (28.37)
0.247	110.80 (5.77)	130.81 (8.60)	178.77 (20.38)
0.352	90.95 (5.02)	108.48 (6.75)	146.38 (14.16)
0.502	69.78 (3.81)	82.33 (5.20)	102.14 (9.74)
0.714	59.41 (3.21)	67.92 (4.26)	81.64 (8.18)
1.017	46.87 (2.64)	54.92 (3.78)	64.45 (6.39)
1.448	37.11 (2.51)	44.08 (3.47)	53.11 (5.13)
2.061	29.56 (2.45)	34.58 (3.15)	38.16 (4.82)
2.935	24.16 (2.22)	28.15 (2.86)	33.75 (3.63)
4.178	19.66 (2.10)	22.13 (2.57)	24.72 (3.15)
5.946	15.40 (1.98)	17.57 (2.52)	19.47 (3.19)
8.466	10.85 (1.56)	12.31 (1.93)	14.62 (2.42)
12.057	7.44 (1.23)	8.21 (1.43)	8.98 (1.73)
17.162	4.29 (1.04)	4.66 (1.18)	5.52 (1.59)

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Table 3. SDSS PROJECTED CORRELATION FUNCTION MEASUREMENTS: RED GALAXIES. Same as Table 1, but for the red galaxy samples.

r_p	9.8	10.2	10.6
0.122	403.78 (18.80)	521.56 (25.91)	646.61 (32.25)
0.173	320.76 (15.07)	405.55 (19.47)	454.60 (24.62)
0.247	250.04 (14.57)	314.75 (18.65)	342.78 (19.72)
0.351	195.97 (13.40)	242.73 (16.24)	260.54 (16.80)
0.500	151.47 (11.28)	184.98 (13.38)	195.04 (14.68)
0.712	116.21 (9.41)	138.60 (11.13)	143.84 (12.16)
1.014	84.82 (7.57)	100.96 (9.10)	104.03 (9.52)
1.445	61.24 (5.95)	71.08 (6.97)	74.22 (7.36)
2.058	45.65 (5.09)	52.60 (5.91)	55.91 (6.11)
2.933	35.51 (4.15)	40.45 (4.80)	44.06 (4.96)
4.175	27.69 (3.49)	30.78 (3.87)	32.02 (3.78)
5.942	20.58 (2.91)	22.73 (3.33)	23.34 (3.28)
8.464	14.31 (2.19)	15.71 (2.46)	16.90 (2.54)
12.048	9.67 (1.56)	10.57 (1.72)	11.10 (1.83)
17.158	5.63 (1.28)	5.96 (1.41)	6.27 (1.55)

Table 4. SDSS GALAXY-GALAXY LENSING MEASUREMENTS: ALL GALAXIES. The first column is the the mean radii of galaxies in each logarithmic bin, in units of $h^{-1}\text{kpc}$. Subsequent columns show the galaxy-galaxy lensing signal, $\Delta\Sigma$, in units of $hM_\odot\text{pc}^{-2}$ for the same three stellar mass, volume-limited threshold samples. Errors in the parenthesis are derived from dividing the survey area into 200 bootstrap subregions and generating 500 bootstrap-resampled datasets.

R	9.8	10.2	10.6
22.31	63.70 (21.61)	74.42 (22.62)	107.60 (35.44)
27.25	30.06 (17.22)	38.67 (20.61)	66.02 (30.09)
33.28	73.26 (13.96)	82.86 (16.32)	93.90 (22.64)
40.65	44.88 (12.16)	53.44 (13.74)	50.51 (20.24)
49.65	28.61 (9.98)	32.43 (10.95)	36.85 (15.80)
60.64	21.14 (7.67)	18.12 (8.63)	31.80 (12.23)
74.07	24.35 (5.80)	19.22 (6.82)	30.23 (10.61)
90.47	15.46 (5.48)	15.01 (6.16)	29.77 (8.42)
110.50	7.42 (4.60)	11.58 (5.27)	18.38 (6.51)
134.96	9.16 (3.55)	11.49 (4.30)	16.27 (6.25)
164.84	6.50 (3.02)	8.92 (3.48)	9.30 (4.61)
201.34	8.04 (2.28)	10.52 (2.76)	18.22 (3.98)
245.92	6.10 (1.97)	6.34 (2.24)	8.01 (3.47)
300.36	5.52 (1.44)	7.87 (1.75)	11.24 (2.44)
366.86	5.46 (1.32)	6.33 (1.58)	7.18 (2.21)
448.09	6.39 (1.06)	6.80 (1.28)	7.60 (1.90)
547.30	4.87 (1.08)	4.75 (1.26)	6.17 (1.71)
668.47	4.80 (0.81)	5.65 (0.93)	5.28 (1.30)
816.47	4.30 (0.78)	5.36 (0.91)	5.71 (1.19)
997.24	3.14 (0.66)	3.53 (0.74)	4.78 (0.97)
1218.03	3.38 (0.62)	4.15 (0.69)	4.26 (0.92)
1487.70	2.45 (0.49)	2.61 (0.60)	2.58 (0.70)
1817.09	2.26 (0.45)	2.44 (0.54)	2.21 (0.68)
2219.40	1.94 (0.38)	2.20 (0.43)	1.98 (0.48)

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Table 5. SDSS GALAXY-GALAXY LENSING MEASUREMENTS: BLUE GALAXIES. Same as Table 4, but for the blue galaxy samples only.

R	9.8	10.2	10.6
22.31	6.48 (26.63)	7.84 (33.83)	-13.01 (49.56)
27.25	45.09 (24.06)	58.31 (32.65)	80.30 (51.75)
33.28	63.59 (18.76)	66.80 (23.73)	92.62 (40.50)
40.65	23.37 (16.81)	30.48 (20.99)	28.38 (34.65)
49.65	29.98 (13.69)	28.97 (16.74)	31.42 (24.16)
60.64	14.40 (9.90)	8.98 (12.68)	21.85 (18.54)
74.07	26.14 (7.77)	20.19 (10.48)	30.27 (16.33)
90.47	11.48 (7.59)	14.53 (10.79)	36.54 (14.80)
110.50	4.26 (5.64)	12.35 (7.42)	25.49 (11.25)
134.96	5.36 (4.89)	7.00 (6.18)	14.19 (9.68)
164.84	0.17 (4.29)	3.90 (5.58)	0.87 (8.74)
201.34	2.07 (3.19)	3.46 (4.27)	10.81 (6.29)
245.92	2.92 (2.97)	1.68 (3.48)	1.99 (5.43)
300.36	3.14 (2.29)	4.94 (3.00)	10.39 (4.27)
366.86	2.93 (1.74)	3.15 (2.21)	1.52 (3.39)
448.09	4.08 (1.48)	3.25 (2.06)	4.04 (3.00)
547.30	3.03 (1.17)	2.17 (1.61)	1.79 (2.42)
668.47	2.06 (0.91)	2.62 (1.22)	4.11 (1.92)
816.47	2.02 (0.88)	2.69 (1.12)	3.02 (1.89)
997.24	1.26 (0.78)	1.50 (1.02)	3.94 (1.41)
1218.03	1.33 (0.59)	2.24 (0.81)	2.91 (1.29)
1487.70	1.50 (0.51)	1.91 (0.69)	2.48 (1.04)
1817.09	1.23 (0.44)	1.19 (0.56)	1.25 (0.89)
2219.40	0.77 (0.36)	0.96 (0.40)	1.15 (0.59)

Table 6. SDSS GALAXY-GALAXY LENSING MEASUREMENTS: RED GALAXIES. Same as Table 4, but for the red galaxy samples only.

R	9.8	10.2	10.6
22.31	121.96 (31.69)	122.83 (33.07)	177.63 (48.40)
27.25	22.89 (27.23)	31.53 (28.54)	75.07 (39.61)
33.28	99.86 (19.59)	109.25 (20.74)	111.89 (28.98)
40.65	68.48 (16.84)	73.14 (17.25)	68.05 (24.40)
49.65	28.77 (14.60)	37.25 (14.99)	40.52 (20.49)
60.64	29.27 (11.08)	26.06 (11.38)	38.25 (17.29)
74.07	25.52 (8.76)	22.61 (9.61)	36.02 (14.13)
90.47	20.70 (7.36)	15.64 (7.56)	30.91 (10.31)
110.50	8.68 (6.97)	9.41 (6.94)	12.21 (9.30)
134.96	13.76 (5.82)	15.03 (6.14)	17.82 (8.18)
164.84	14.43 (4.04)	12.43 (4.27)	15.32 (5.47)
201.34	16.12 (3.39)	17.13 (3.62)	23.43 (5.01)
245.92	9.35 (2.61)	9.46 (2.80)	11.08 (4.00)
300.36	9.97 (2.14)	11.33 (2.30)	13.67 (3.22)
366.86	8.36 (1.91)	8.83 (2.00)	10.65 (2.98)
448.09	8.84 (1.66)	9.18 (1.82)	9.62 (2.44)
547.30	7.07 (1.55)	6.77 (1.65)	8.73 (2.22)
668.47	7.87 (1.24)	7.69 (1.30)	6.02 (1.72)
816.47	7.15 (1.07)	7.51 (1.05)	7.89 (1.30)
997.24	5.27 (0.98)	5.09 (0.96)	5.31 (1.16)
1218.03	5.70 (0.94)	5.66 (0.94)	5.17 (1.08)
1487.70	3.53 (0.79)	3.19 (0.79)	2.79 (0.91)
1817.09	3.33 (0.75)	3.23 (0.78)	2.70 (0.86)
2219.40	3.44 (0.63)	3.31 (0.62)	2.65 (0.64)

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